Influence of Urban Landscape Characteristics on Riparian Forest Structure

Undergraduate Honors Thesis

Presented in Fulfillment toward the Requirements for a Bachelor of Science Degree with Honors Research Distinction from The Ohio State University

Written By

Lillian Ostrander

School of Environment and Natural Resources

Advised By

Dr. Stephen Matthews

School of Environment and Natural Resources

The Ohio State University

Spring 2021

Thesis Committee

Stephen N. Matthews, PhD

Matthew L. Hamilton, PhD

Elizabeth Myers Toman, PhD

Abstract

Riparian forests benefit the local communities in which they exist by providing ecosystem services, contributions made through natural functions and processes that assist humans. As urban encroachment on these forests grows with increasing urban populations, it is crucial to understand and manage riparian forests effectively in order to retain these functions. Because urbanization exerts pressures on a landscape scale, human development becomes the dominant matrix condition in which these forests exist. Most ecological studies that quantify urbanization metrics account for physical characteristics of the landscape, but few involve anthropogenic and social variables. This study was conducted to identify components of the neighborhoods surrounding urban forests that may influence vegetation structure and diversity. The sites used in this analysis were urban riparian forests around Columbus, Ohio with a rich history of research on restoration and avian communities' response to urban landscapes. This study utilized historical vegetation survey data paired with census data regarding the surrounding neighborhoods. Linear models were constructed in order to identify significant relationships between census variables and response variables concerning basal area and a diversity index of the forests. After using an information-theoretic approach to assess the relevance of each model, it was found that forests within areas of newer development tended to have lower basal areas and less diversity than those within older neighborhoods. Several models were found to capture a significant amount of the variation in the dataset, including those containing variables such as total population and a previously calculated urban index value accounting for land cover and number of buildings. The results of this study suggest that additional variables concerning the neighborhoods around forest sites could be useful to include in urbanization metrics. These datasets are often widely available online to the public and could add meaningful dimensions to future analyses on urbanization impacts on riparian forests.

Acknowledgments

I would like to extend my heartfelt thanks to Dr. Matthews for providing me the opportunity to engage in this research. His guidance and support throughout the last several years while working on this project has been invaluable. Sincere thanks as well to my committee members, Dr. Myers Toman and Dr. Hamilton, for their feedback during my defense and contributions to the final version of this thesis. I would like to acknowledge the land used for this research is the ancestral homeland of the Shawnee, Potawatomi, Peoria, Seneca, Wyandotte, Ojibwe, Cherokee, and other Indigenous nations and peoples. The ideas for this project were developed while working under financial support provided by the U.S. Department of Agriculture Forest Service through agreement 17-CA-11132546-023.

Table of Contents

Introduction

The process of urbanization, the growth of cities and transition of human populations into urban environments, has the potential to drastically alter ecological systems. It is estimated that two-thirds of the global population will live in an area classified as urban by the year 2050, signaling a shifting trend that will necessitate a change in the way urban environments are managed (UN, 2014). Extending urban development can impact forests and vegetation directly by replacing formerly "natural" areas with housing, commercial buildings, or pavement (Pennington et al. 2010). The consequences of these changes can indirectly impact vegetation by changing hydrology patterns, fragmenting patches of forest, and impacting other biological communities that reside there (Hahs and McDonnell, 2007).

The removal and uptake of nutrients, stabilization of riverbanks guarding against erosion, and flood control are all examples of ecosystem services provided by riparian forests, benefits provided by a particular ecosystem to local communities and economies (Boyd & Banzhaf, 2007). Riparian forests are particularly important to environmental health and function because of their ability to enhance water security, particularly in urban areas (Ilhardt et al. 2000). Eutrophication, pollution, erosion, and flooding have been identified as some of the most harmful water quality issues, causing billions of dollars of damage to water bodies annually (Ribaudo et al. 1999, Ribaudo, 1986, Klapproth and Johnson, 2009). Direct effects of urbanization threaten to decrease ecosystem services through the removal of riparian forests, but indirect effects can still impact the function of these forest ecosystems (Pennington et al. 2010). A study conducted in the Georgia Piedmont found that urban landscapes were associated with decreased stem densities and regeneration potential in riparian forests (Burton and Samuleson, 2008). These results emphasize the importance of considering the surrounding landscapes when analyzing riparian forest structure to identify factors behind within stand forest changes (Burton and Samuelson, 2008). Increasing understanding of drivers of forest diversity and structural change is crucial to forest management in increasingly urban settings.

Acknowledging urban spaces as complex with variable characteristics is an important step in identifying site-specific solutions for urban forestry management and in identifying the drivers of ecological change. While there is a pattern of variation in forest structure and diversity along urban to rural gradients, narrowing in on the specific drivers of these changes can be a challenge. One contributing factor is the lack of standardization of the definition of "urbanization." How urbanization is quantified in studies on this subject is a critical component that must capture ecological and social dimensions. The ways in which other studies model urban landscapes can vary, ranging from focusing on one metric such as impervious surface to using principal component analyses to combine multiple variables (Moll et al. 2019). The results of these studies can be difficult to generalize and the heterogeneity within urban landscapes can complicate management decisions (Pennington et al. 2010). Applications of urban forest research that are too broad ignore the intricacy of the urban ecological system. One component of the urban ecosystem that is frequently left out is the human component. Humans are the primary drivers behind land-use change and urbanization but are often overlooked in analyses when quantifying differences in vegetation. A recent meta-analysis suggested only about 6% of urban ecology studies directly involve human dimensions in their measures of urbanization (Moll et al. 2019). The recommendations found in Moll et al. (2019) included suggestions to incorporate socio-economic variables and other measures of human heterogeneity in future studies in order to develop a broader, more inclusive view of urban ecology.

Columbus, Ohio is the 14th largest U.S. city with over 900,000 residents, (City of Columbus, 2021). The Mid-Ohio Regional Planning Commission anticipates a population of roughly 3 million people in central Ohio by 2050 (City of Columbus, 2021). This population growth is expected to accelerate urbanization processes, potentially directly and indirectly impacting vegetation. The City of Columbus Recreation and Park Department has identified tree cover throughout the city as being important to consider as the city expands. As of 2013, city-wide tree cover amounted to only 22%, a low number when compared to cities like Pittsburgh, PA and Charlotte, NC, both of which have greater than 40% tree canopy cover (City of Columbus, 2021). The growing city of Columbus therefore provides an ideal location for studying urban forests given that the management of those forests is a pressing and relevant topic in local government. The Columbus Urban Forestry Master Plan also determined that tree cover is unevenly spread throughout the city, showing some neighborhoods have as little as 9% canopy cover, while others have as high as 41% (City of Columbus, 2021). This data shows that there is a great deal of heterogeneity in Columbus' forests and that social equity factors in the neighborhoods surrounding the forests can impact the total tree cover in a given area. Equitable distribution of tree cover throughout the city would ensure that every neighborhood can enjoy the ecosystem services provided by forest systems in urban areas.

This study analyzes the structure and composition of seven urban riparian forest sites in Columbus, Ohio, attempting to relate data about the surrounding communities to vegetation metrics. The sites selected for this study were supported by a vast body of research done in the last twenty years regarding urbanization and avian communities (Borgmann and Rodewald, 2005, Rodewald and Matthews, 2005, Rodewald et al. 2015). These studies utilized sites along an urban-rural gradient, with the majority of sites falling somewhere in between the two extremes on the continuum. The sites selected for this study generally had more urban and suburban characteristics, although they still existed on the gradient and had varying degrees of urbanization. The primary objective of this study was to assess patterns in forest composition in sites all classified as urban, but with varying degrees of urbanization. It was hypothesized that if there were differences in the characteristics of the neighborhoods surrounding each site, there would be corresponding differences in forest structure and diversity in the forests within them. Given the significant role of humans in ecosystems and the relative scarcity of urban ecology studies including human dimensions, this study included census data to identify trends in neighborhoods. It was predicted that because humans are drivers of urbanization, neighborhood characteristics would vary along with the differences in structure and diversity between urban forest sites. Understanding the specific variables within urban neighborhoods that contribute to variation in urban forests will become important for ecological management in expanding cities as the interactions between humans and the environment grow and become more complex.

Methods

Site Selection

In this study I am building off of prior work investigating riparian forest patches in the Columbus, Ohio area along a rural-urban gradient. This long-term ecological perspective of addressing forest bird responses to urbanization provided an ideal background in which to continue further research. A core component of these previous studies used an urban index value to rank each site on an urban index scale ranging from -1.73 to 1.75 (Rodewald and Shustack, 2008). These values, initially calculated in 2008, were derived from a principal component analysis, weighting positively for traditionally urban characteristics such as number of buildings, road, lawn, and pavement cover, and weighted negatively for agriculture and forested land cover (Malpass et al. 2015). Therefore, large negative urban index values indicated a site with more rural characteristics, while larger positive values showed more urban sites. Although the vegetation data used was collected in 2011, the values calculated for the urban index values were not expected to change significantly in the three years between 2008 and 2011 and therefore would still be appropriate to use in this study. Ultimately, seven sites were selected with urban index values between -0.16 and 1.61 (Table 1).

Table 1 Values for urban index obtained using methods from Rodewald and Shustack (2008). Urban index values are derived from a Principal Component Analysis using land cover and number of buildings to assess the setting of each site. Table values used calculated in Malpass et al. (2015).

Site	Urban Index Value
Elk Run	-0.16
Cherry Bottom	0.76
Woodside	0.32
Rush Run	0.75
Kenny	0.89
Casto	1.25
Tuttle	1.61

These seven riparian forests vary slightly in width and are positioned along either the Olentangy River, Alum Creek, or Big Walnut Creek in Franklin County (Figure 1).

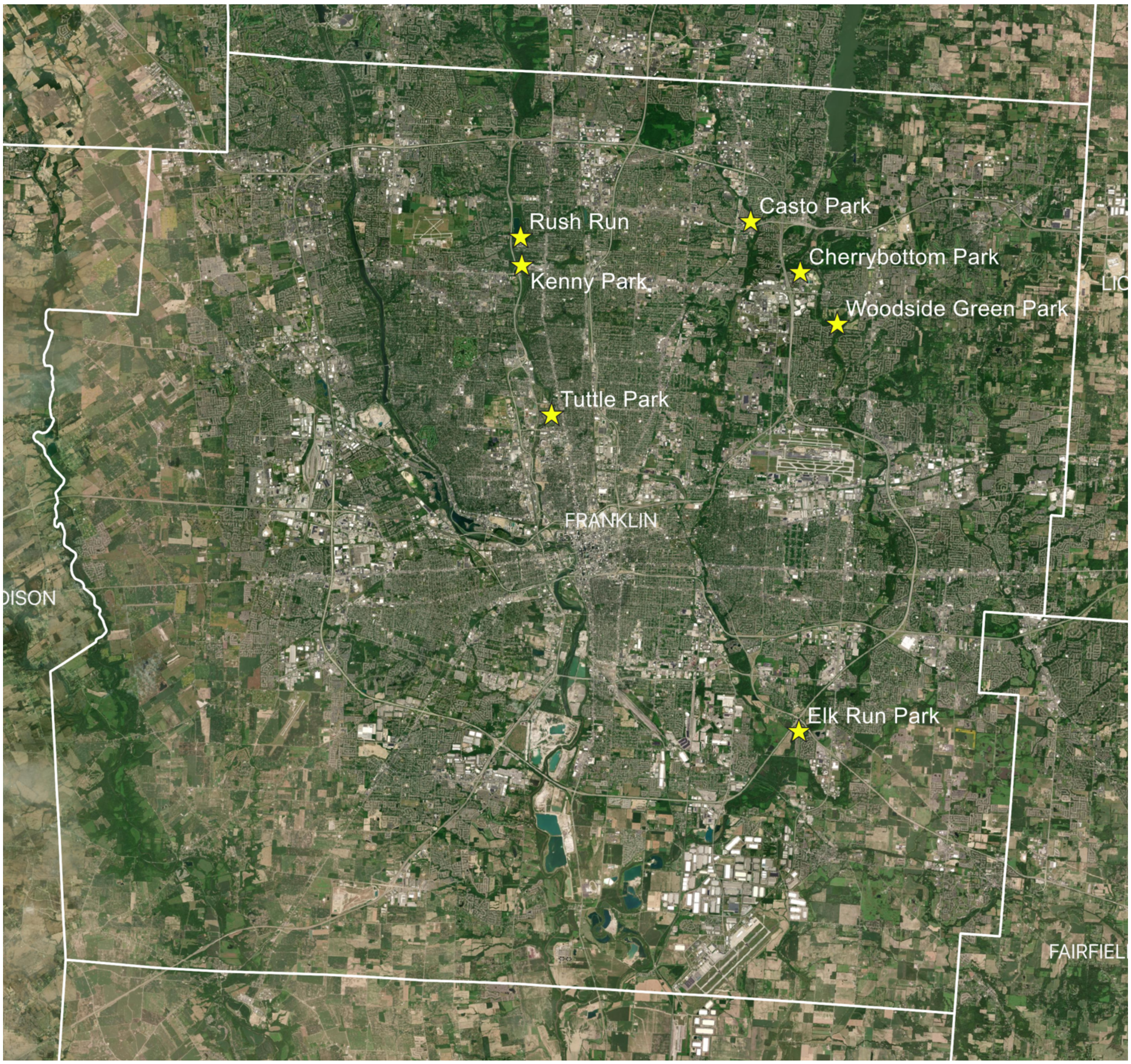

Figure 1: Map depicting the locations of all 7 urban riparian sites used in this study within Franklin County, Ohio. This map was created using ESRI satellite imagery retrieved 2/16/21.

Data Collection

The data to measure forest structure was collected in the summer of 2011 in uniformly sized plots throughout each site. Circular 0.04-ha plots were located 50 meters apart along a transect 20 meters from and parallel to the water, with 4-8 plots per site (Rodewald and Matthews, 2004). Each tree within the plot was identified to species and then measured at the diameter at breast height (DBH); the data was binned by size class, categorizing them into small (8-23 cm), medium (23-28 cm), and large (>38 cm) classes (Rodewald and Matthews, 2004). To summarize these data, the basal area and Shannon Diversity Index were calculated for each site. The basal area calculation used the midpoint of each size class for an estimate of DBH; the DBH was then squared and multiplied by a conversion factor to convert to feet from inches (0.005454) in order to come up with the final calculation (Bettinger et al. 2017). The Shannon Diversity Index was calculated in R using the 'vegan' package by applying the 'diversity' function to a table of species counts in each site. The measure of Shannon Diversity Index was calculated from species counts in each site in a method that accounts for both species richness and evenness across the site. This ensures that both the number of species and their distribution across a site are accounted for, making it a more reliable metric compared to simple species richness measurements. These metrics of forest structure were later used in the data analysis as response variables.

Information regarding the surrounding communities was obtained by utilizing open-source data from the US Census Bureau. To define the neighborhoods surrounding the sites, a 1-kilometer buffer was created around the center-point of each site in QGIS. The buffers were set to overlay a map containing the census tracts within Franklin County, Ohio to determine the tracts involved in each site. An example of this process is demonstrated below in Figure 2, showing the 1-km buffer and census tract boundaries for Tuttle Park. Similar maps for the six other sites are also available (Appendix Fig. A.1.1-A.1.5).

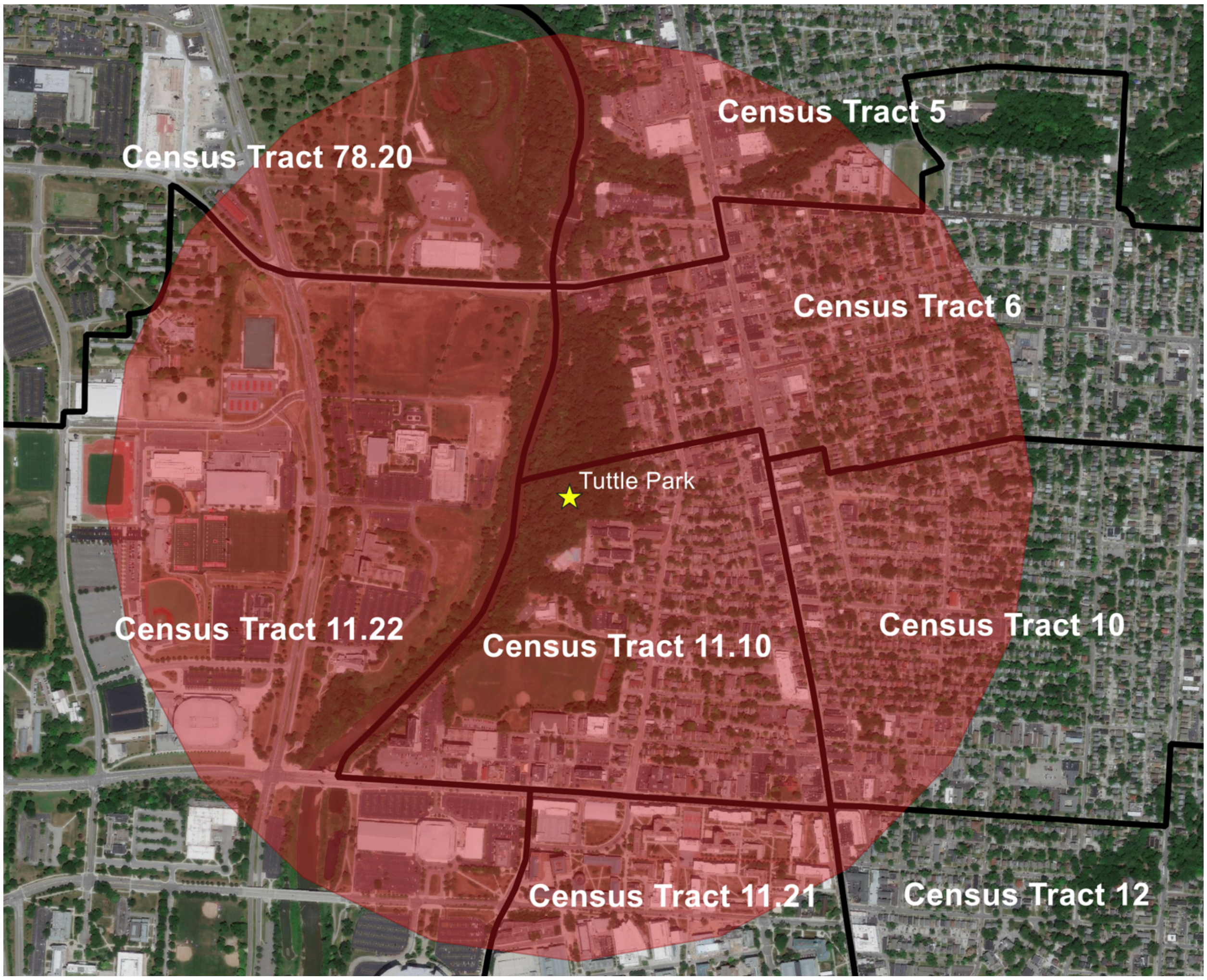

Figure 2: Map of the 1-km buffer zone created around the center of Tuttle Park in Columbus Ohio, displayed here in red. The census tracts are labeled, the boundaries being the black lines for 2011 census period.

Data for each census tract involved was then collected using the US Census Bureau's Social Explorer tool, downloading all data needed at the census tract level. The dataset used was the American Community Surveys' 5-year estimates, using the years 2007-2011 as the focus. The final average values for each site were calculated by weighting each census tract relative to the percentage of the 1-km buffer it occupied and multiplying the data values by that proportion. This final average values for each variable were the values used in further analyses (Appendix Table A.2). A review of available census data led to the selection of several variables to include in models during further analysis (Table 2).

Table 2 Definitions of the independent variables used in the data analysis

Variable	Definition
age	Average age of population
val	Median house value for owner-occupied housing units
inc	Median household income
dens	Population density
rent	Median rent payments on rented properties
totp	Total population
perr	Percent of housing units within buffer rented instead of owned
yb	Average year structures built
urb	Urban index values (Rodewald & Shustack, 2008).

After the weighted averages for each variable were calculated, a test for correlation was conducted to ensure there was sufficient variation present in the data (Appendix Table A.1). Combinations of variables with correlation coefficients greater than |0.6| were eliminated. Models with single variables were constructed first from variables that were not strongly correlated with one another. Combinations of these variables were then paired together, then narrowed down to ensure a relatively equal distribution of variables amongst the ten models. This process resulted in ten models: four single variable models, four models with 2 variables per model, and two models with 3 combined variables (Table 3).

Table 3 Definitions of each linear model referenced in the results, including the variables included in each model.

Model Number	Variables Included
1	Age
2	Total Population
3	Urban Index
4	Year Built
5	Total Population + Age
6	Urban Index + Age
7	Year Built + Age
8	Total Population + Urban Index
9	Age + Urban Index + Total Population
10	House Value + Urban Index + Year Built

Data Analysis

The ten selected models were tested assuming linear relationships using basal area and the Shannon Diversity Index on the site level as response variables. To meet the normality assumption of the linear models, the response variables were transformed using a log function. The normality of the datasets was confirmed using Shapiro-Wilks tests (p=0.1). The Akaike Information Criterion (AIC) was then calculated for each reasonable model tested to assess how well the models fit the data used relative to one another, which included a correction for the small sample size of sites used. An information-theoretic approach was used to assess the relevance of each model as outlined in Burnham et al. (2011). This involved calculating Δ AICc values for all models, with ΔAICc being the difference between the lowest AICc and the remaining models' AICc values. The Δ values were used to compare models and choose the relative best fit model based on Burhnam et al. (2011) thresholds: Δ values greater than 9 have little support relative to other models, but models with Δ values between 0 and 9 may still be plausible models. Models with low AICc values were interpreted to have the least amount of information loss and fit the dataset best.

Results

Testing each model with each of the two response variables resulted in several competitive models in the candidate set (Table 4). However, model 4, representing year built on its own, had the most support and was found to be significant when related to both basal area and Shannon Diversity Index ($p=0.008$, $R^2=0.737$ and $p=0.081$, $R^2=0.384$ respectively). Model 2, containing total population, was identified as having a strong significant relationship with basal area ($p=0.054$). Model 4 showed the greatest significant relationship out of all ten models (Figure 3, Figure 4)

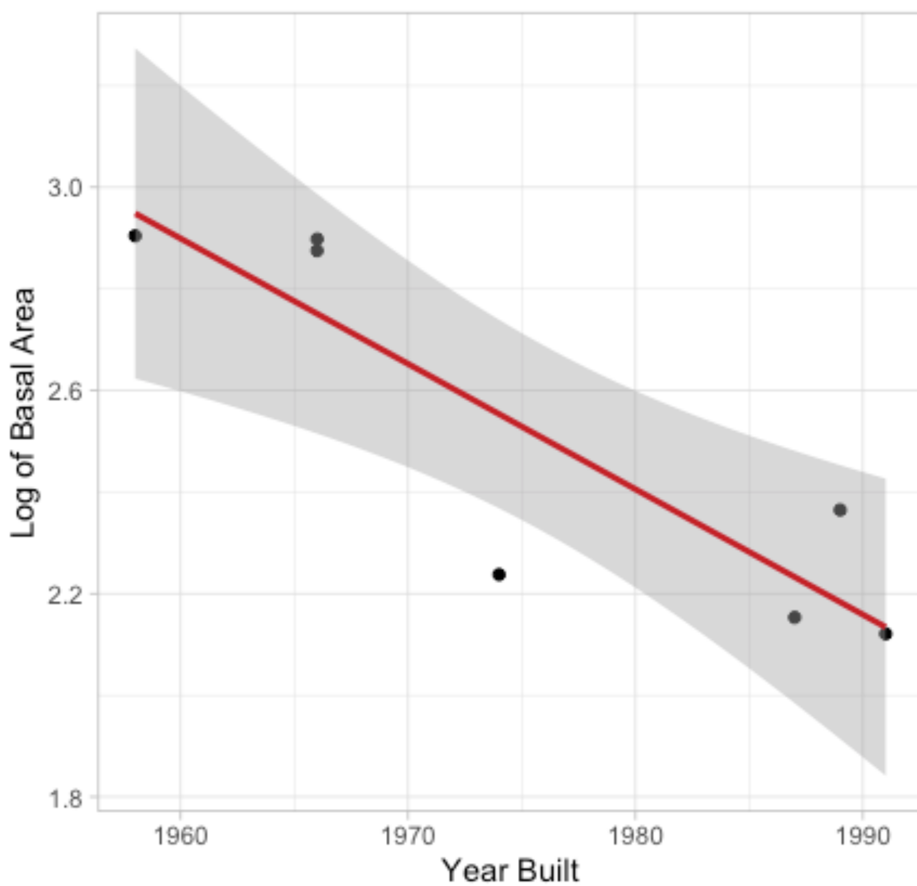

Figure 3 Linear relationship between the year built and the transformed basal area, graphed with the standard error, for urban riparian forests in Columbus, Ohio.

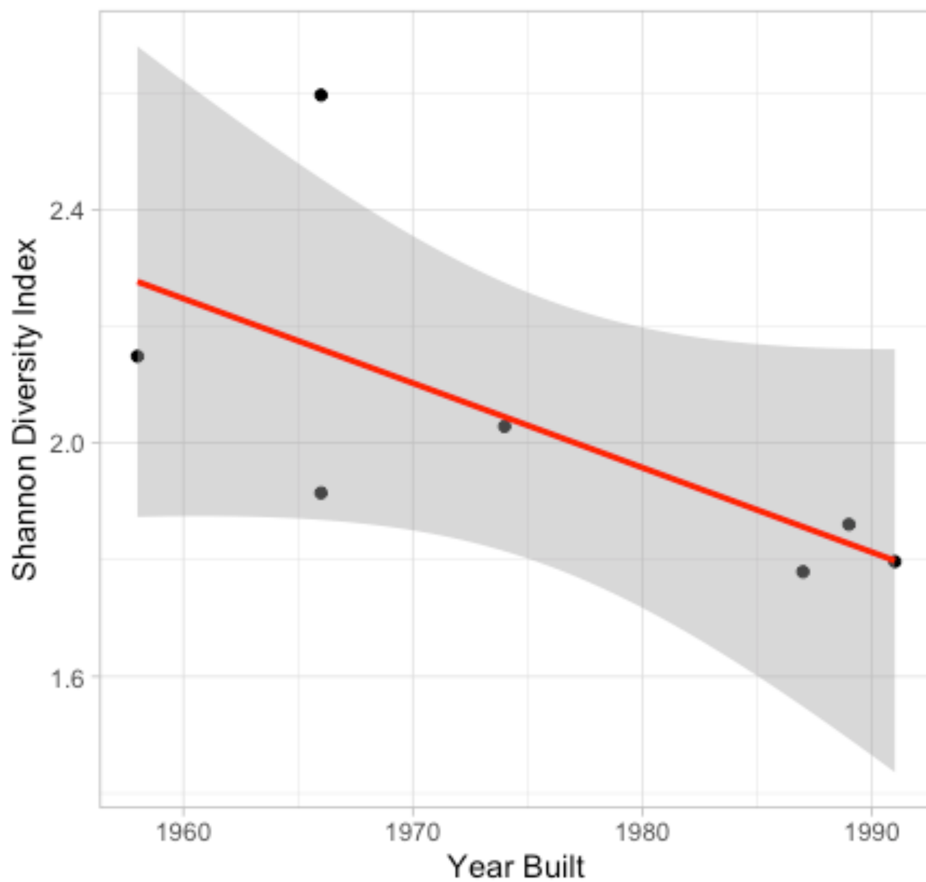

Figure 4 Linear relationship between the year built and the Shannon Diversity Index, graphed with the standard error, for urban riparian forests in Columbus, Ohio.

The models with multiple variables involved resulted in several significant interactions as well. Model 7 was identified as having a strong significant relationship with basal area ($p=0.02041$, $R^2=0.7857$), where the model included two variables: year built and age together. Model 10, which combined house value, urban index, and year built into one model, also had a strong significant relationship with basal area and a notably high R^2 value ($p=0.02459$, $R^2 = 0.8797$).

Table 4 Results from candidate model set of basal area and Shannon Diversity Index reporting the p-values, adjusted R^2, and AICc values. Variables used in each model are printed in Table 3. One asterisk, "*", signifies a marginal significance (p<0.1), "**" signifies a strong marginal significance (p<0.05), and "***" signifies a very strong marginal significance (p<0.01).

	Basal Area			Shannon Diversity Index		
Model	P-value	R^2	AICc	P-val	R^2	AICc
1	0.4701	-0.06951	17.99403	0.3891	-0.01886	-8.314516
2	0.05424**	0.4498	13.34141	0.1289	0.2772	-10.71755
3	0.228	0.1287	16.55936	0.3597	0.002721	-8.46435
4	0.008318***	0.7371	8.172931	0.08154*	0.3836	-11.83241
5	0.2102	0.3123	27.34062	0.3445	0.1196	3.101083
6	0.2237	0.2906	27.55831	0.3021	0.1756	2.641238
7	0.02041**	0.7857	19.17841	0.1549	0.4096	0.304312
8	0.1971	0.334	27.1164	0.3589	0.1014	3.244199
9	0.4027	0.1534	68.78227	0.5476	-0.07481	44.48395
10	0.02459**	0.8797	55.12447	0.347	0.2427	42.03289

The AICc values provide a measure of relative fit of each model to the datasets provided. Comparing each model using the information-theoretic approach from Burnham et al. (2011) led to model 4 being selected as the preferred model with the least amount of data loss for both basal area and Shannon diversity; this model had the lowest AICc value for both response variables, with the next highest AICc values being 5.17 and 1.11. When Shannon diversity was used as the response variable, all of the other single-variable models had Δ values of less than 9, suggesting they could be plausible compared to the other models. With basal area as the response variable, models 2 and 3 were also found to have Δ values of less than 9, identifying them as plausible models as well.

Table 5 AICc and ΔAICc values for each of the models tested. The AICc values were taken by subtracting the lowest AICc (in this case, the value for model 4) from the calculated AICc for each model.

	Basal Area		Shannon Diversity	
Model	AICc	ΔAICc	AICc	ΔAICc
1	17.99403	9.821099	-8.314516	3.517894
2	13.34141	5.168479	-10.71755	1.11486
3	16.55936	8.386429	-8.46435	3.36806
4	8.172931	0	-11.83241	0
5	27.34062	19.167689	3.101083	14.933493
6	27.55831	19.385379	2.641238	14.473648
7	19.17841	11.005479	0.304312	12.136722
8	27.1164	18.943469	3.244199	15.076609
9	68.78227	60.609339	44.48395	56.31636
10	55.12447	46.951539	42.03289	53.8653

The lowest AICc values for basal area were found in models 2 and 4, which tested year built (AICc=8.172931) and total population (AICc=13.34141). Other notable models that exhibited relatively low AICc scores were the models 1 (AICc=17.99403) and 3 (AICc=16.55936). Model 4, the model that returned the greatest marginal significance and lowest AICc value, suggests a statistically significant decrease in basal area in sites where the neighborhoods were constructed more recently (Figure 3). The resulting AICc, R^2, and p-values from model 2 also suggest that as the total population around these forest sites increase, basal area tends to decrease (Figure 5).

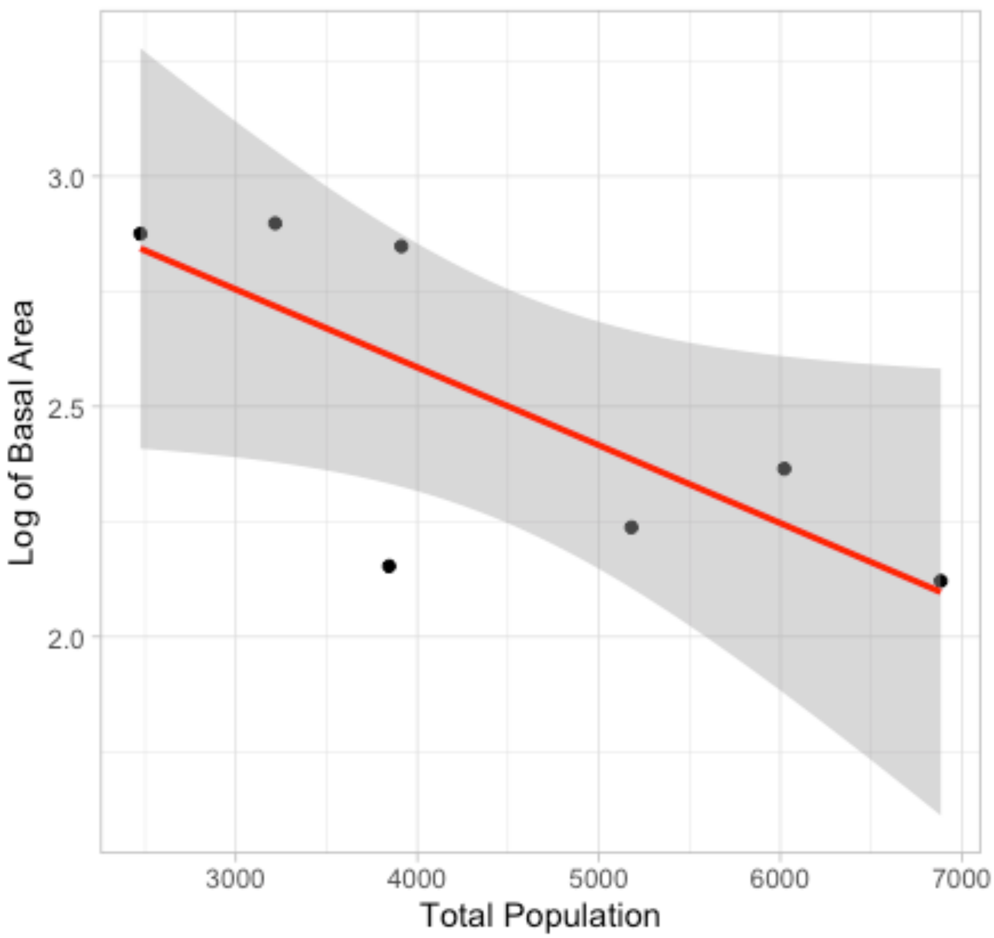

Figure 5 Graph depicting the linear relationship between total population and the transformed basal area, graphed with the standard error.

Discussion

The analysis of each model indicates a very strong relationship between year built and the structure and diversity of these urban forests (Appendix Tables A.3, A.4). The year built variable reflects the median age of the structures within 1 km of each site, with values ranging from 1958 to 1991. This study suggests that more recently built neighborhoods show decreases in forest basal area and diversity. Similar findings were established in Conway & Bourne (2013), which found greater canopy cover in older neighborhoods and lower levels of canopy cover in neighborhoods with more recent development. Although the response variable used in their study was canopy cover and not basal area, these findings still suggest an increase in vegetation presence based on the age of neighborhoods and relates to the results of this study as well. Increased levels of basal area and diversity measures in older neighborhoods could reflect older, more established forests due to prior planting efforts in addition to more distant disturbance events (Conway & Bourne, 2013). Because these forests were not planted and are more likely the remnant patches of larger forests that were there before, planting efforts would not apply in this scenario. One potential explanation could be that neighborhoods were initially built in more diverse forests, where newer neighborhoods were built around the remaining forest patches that were lower in basal area or had decreased diversity. Decreases in basal area with more recent development could also be a sign of more recent human disturbance from construction, potentially altering hydrology and the presence of exotic species (Pennington et al. 2010). Where the forests in older neighborhoods may have had sufficient time to recover from disturbance events, more recently disturbed forests may not yet have had that time.

The second-best model according to its AICc value was model 2, a single variable model testing the relationship between basal area and total population. This finding suggests that forests within neighborhoods with greater populations have lower basal areas than those with fewer people. This finding corroborates prior research that found population density to be the best predictor of riparian vegetation cover (Grove et al. 2006). This variation in basal area between sites suggests structural differences that could be attributed to greater disturbance and human influence on forests where there are more people that live in the surrounding area. For instance, total population could be highly associated with greater levels of development in the surrounding area, leading to altered hydrology and therefore impact the types of trees as well as their locations within the forest. Forests in closer proximity to large populations could also be more frequently utilized as recreation spaces. Recreation impacts on urban forests were quantified in Ballantyne & Pickering (2015), whose work found that structural impacts could result from both formal and informal trails being used by surrounding populations. These impacts were found to be particularly important to consider in the fragmented forest patches common in urban areas (Ballantyne & Pickering, 2015). Using total population as an indicator of recreational intensity and therefore forest structure and health could then be valuable to future management decisions, but further research should be conducted to support that connection. Additionally, a greater number of people living around forests could help facilitate growth of exotic species, another factor that could significantly impact the composition of these sites.

The values for basal area calculated from each site could be impacted by exotic, invasive species such as honeysuckle that are common in many of the selected sites. A similar study regarding riparian forests in the urban landscape of Cincinnati, Ohio found that the presence of exotic species such as *Lonicera maackii* was strongly associated with urban encroachment on forest patches (Pennington et al. 2010). This association has been repeatedly shown in other studies as well, suggesting that increasingly urban environments could be facilitating the spread of non-native invasive species (Burton & Samuelson, 2007). The presence of *Lonicera maackii* in the sites used in this study could be affecting the basal area measurements because of its aggressive growth and negative impact on regeneration potential for native trees and shrubs. Forests dominated by *Lonicera maackii* have been shown to have significantly decreased basal area overall and show reduced growth rates of overstory trees' basal areas by up to 53% (Hartman and McCarthy, 2007). The effects of surrounding neighborhoods and increased urbanization on forest structure could be exacerbated by the presence of these invasive species that are known to alter basal area and dominate the understory and midstory layers of urban forests. It is important, then, to address the presence of invasive species as a factor that works in conjunction with external factors and cannot be separated from the discussion, particularly because honeysuckle was listed in the most abundant species for several of the sites in this study (Appendix Table A.5). The presence of honeysuckle in these sites results in a strong impact on avian productivity as evaluated by Rodewald and Shustack (2008).

It is also important to note that this information-theoretic approach penalizes the addition of variables into a model quite substantially. Therefore, it may still be notable that models 7 and 10 produced strongly significant p-values despite having calculated AICc values that may indicate these models are not supported. Models 7 and 10 incorporate two and three variables respectively instead of the single variable models that routinely produced the lowest AICc values. These multi-variable models may then still be relevant to our understanding of external factors influencing forest structure even if they are not the overall preferred model using the information-theoretic approach. Further research should be conducted with increased sample sizes in order to determine whether the more complex models are supported.

Overall, this study suggests that certain characteristics of the neighborhoods adjacent to urban forests can help inform preliminary ideas about urban forest structure and composition. These characteristics cannot always be categorized as simply as “urban vs. rural”; rather, there is a great deal of heterogeneity within urban setting, making it important to take a site-specific approach to forest management. This study also speaks to the significance of understanding forest dynamics in a way that goes beyond analyzing small vegetation plots within a site. Forests, and particularly those in urban areas, are influenced by the landscape in which they are embedded and by the purposes they serve to their communities. It is tempting to think of patches of forest as individual islands in a sprawling urban landscape, but to make that shortcut would be to ignore all context, missing factors that could be contributing to the health or degradation of the ecosystem. Fortunately, the neighborhood characteristics discussed here can be determined from publicly accessible data, making these variables simple but meaningful additions to analyses of urban forests.

Quantifying neighborhood characteristics and incorporating them into vegetation analyses can also help us ensure more equitable distribution of ecosystem services throughout major metropolitan areas as urbanization increases. A meta-analysis of environmental justice literature related to urban forestry found race-based inequity of forest cover to be significant and that the inequities were worsened when public lands were involved (Watkins & Gerrish, 2018). Collecting data about the neighborhoods around forests could illuminate issues in cities regarding the degradation of riparian forests in less affluent areas or in neighborhoods with greater minority populations. This is particularly relevant in the sites used for this study because these are public city parks; the management decisions fall on the City of Columbus, which could include measures to enhance forest structure, diversity, and overall health. While this study was not able to draw connections between neighborhoods' house value or income and forest structure and diversity, this may be an avenue to pursue in future research to ensure that all populations in Columbus and other metropolitan areas reap the benefits of healthy and functioning riparian forests.

Further emphasis should be put on incorporating human dimensions into forest management, especially in urban settings where influence may be higher. Prior research has shown that human dimensions can be a crucial component of the landscape but are rarely directly included in measures of urbanization (Moll et al. 2019). The significance of human-related variables like total population related to basal area in this study is noteworthy and supports the idea that these dimensions should be included in future discussions of urban forest management. Further research should be done to test more external variables and identify additional significant relationships between forest structure and the surrounding neighborhoods. This would benefit the understanding of the forests themselves, but also help to identify inequities regarding forest placement in urban areas. The critical ecosystem services provided by riparian forests can substantially benefit the communities surrounding them, so ensuring forested land is distributed equitably around cities could have an impact on public health outcomes for disadvantaged communities. Finally, in order to construct a more complete picture of these sites, other response variables could also be explored as a way to quantify forest health, e.g., soil metrics, light availability, and invasive species presence. Forest management challenges will present themselves with greater frequency as the global populations expand their cities. Enhancing our understanding of urban forest dynamics and their relationships with surrounding environments will make our cities resilient to these challenges in the midst of growing urbanization.

Literature Cited

Ballantyne, M. and Pickering, C.M. (2015). Differences in the impacts of formal and informal recreational trails on urban forest loss and tree structure. *Journal of Environmental Management*, 159: 94-105.

Bettinger, P., Boston, K., Siry, J. and Grebner, D.L. (2017) Valuing and characterizing forest conditions. In *Forest Management and Planning* (21-63). Academic Press.

Borgmann, K.L. and Rodewald, A.D. (2005). Forest restoration in urbanizing landscapes: interactions between land uses and exotic shrubs. *Restoration Ecology*, 13(2): 334-340.

Boyd, J. and Banzhaf, S. (2007). What are ecosystem services? The need for standardized environmental accounting units. *Ecological Economics.* 63: 616-626.

Burton, M.L. and Samuelson, L.J. (2007). Influence of urbanization on riparian forest diversity and structure in the Georgia Piedmont, US. *Plant Ecology,* 195: 99-115.

Burnham, K.P., Anderson, D.R., and Huyvaert, K.P. (2011). AIC model selection and multimodel inference in behavioral ecology: some background, observations, and comparisons. *Behav Ecol Sociobol,* 65:23-35.

City of Columbus (2021). *Columbus Urban Forestry Master Plan.* (Spring 2021 Public Review Draft). https://www.columbusufmp.org/uploads/2/6/0/6/26062495/columbus_urban_forestry_master_plan_-_public_comment.pdf.

Conway, T.M., and Bourne, K.S. (2013). A comparison of neighborhoods characteristics related to canopy cover, stem density, and species richness in an urban forest. *Landscape and Urban Planning,* 113: 10-18.

Grove, J.M., Troy, A.R., O'Neil-Dunne, J.P.M., Burch Jr, W.R., Cadenasso, M.L, and Pickett, S.T.A. (2006). Characterization of households and its implications for the vegetation of urban ecosystems. *Ecosystems*, 9:578-597.

Ilhardt, B. L., Verry, E. S., and Palik, B. J. (2000). Defining riparian areas. In *Riparian management in forests of the continental eastern United States* (23-42). Lewis Publishers.

Hahs, A.K. and McDonnell, M.J. (2007). Composition of the plant community in remnant patches of grassy woodland along an urban-rural gradient in Melbourne, Australia. *Urban Ecosystems,* 10: 355-377.

Hartman, K.M. and McCarthy, B.C. (2007). A dendro-ecological study of forest overstorey productivity following the invasion of the non-indigenous shrub Lonicera maackii. *Applied Vegetation Science,* 10(1): 3-14.

Klapproth, J.C.& Johnson, J.E. (2009). Understanding the science behind riparian forest buffers: Effects on water quality. *Virginia Cooperative Extension Publications,* 420-151. https://www.pubs.ext.vt.edu/420/420-151/420-151.html

Malpass, J.S. (2015). *Effects of food and vegetation on breeding birds and nest predators in the suburban matrix*. [Unpublished Doctor of Philosophy Dissertation]. The Ohio State University.

Moll, R.J, Cepek, J.D., Lorch, P.D., Dennis, P.M., Tans, E., Robison, T., Millspaugh, J.J., and Montgomery, R.A. (2019). What does urbanization actually mean? A framework for urban metrics in wildlife research. *Journal of Applied Ecology*, 56(5): 1289-1300.

Pennington, D.N., Hansel, J.R., and Gorchov, D.L. (2010). Urbanization and riparian forest woody communities: Diversity, composition, and structure within a metropolitan landscape. *Biological Conservation,* 143(1): 182-194.

Ribaudo, M.O. (1986). Regional estimates of off-site damages from soil erosion. Pages 29-46. In: Waddell, T.E. (editor). *The Off-Site Costs of Soil Erosion.* Proceedings of a symposium held May 1985. Conservation Foundation, Washington, D.C.

Ribaudo, M.O., Horan, R.D., Smith, M.E. (1999). Economics of water quality protection from nonpoint sources: Theory and practice. *Resource Economics Division, Economic Research Service, U.S. Department of Agriculture.* Report number 782.

Rodewald, A.D., Rohr, R.P, Fortuna, M.A., and Bascompte, J. (2015). Does removal of invasives restore ecological networks? An experimental approach. *Biological Invasions,* 17: 2139-2146.

Rodewald, A. D., and Shustack, D.P. (2008). Urban flight: understanding individual and population-level responses of Nearctic-Neotropical migratory birds to urbanization. *Journal of Animal Ecology,* 77:83-91.

Rodewald, P.G. and Matthews, S.N. (2005). Landbird use of riparian and upland forest stopover habitats in an urban landscape. *The Condor,* 107(2), 259-268.

Watkins, S.L, and Gerrish, E. (2018). The relationship between urban forests and race: a meta-analysis. *Journal of Environmental Management,* 209: 152-168.

Appendix:

Table A.1 shows the correlation coefficients between all variables tested.

	Age	House Value	Income	Population Density	Rent	Total Population	% Units Rented	Urban Index	Year Built
Age	1.00	0.86	0.78	-0.55	0.87	-0.44	-0.75	-0.29	-0.06
House Value	0.86	1.00	0.75	-0.37	0.70	-0.50	-0.54	-0.15	-0.03
Income	0.78	0.75	1.00	-0.70	0.75	0.04	-0.89	-0.48	0.37
Population Density	-0.55	-0.37	-0.70	1.00	-0.31	-0.30	0.90	0.86	-0.75
Rent	0.87	0.70	0.75	-0.31	1.00	-0.28	-0.65	-0.16	-0.24
Total Population	-0.44	-0.50	0.04	-0.30	-0.28	1.00	-0.13	-0.58	0.73
% Units Rented	-0.75	-0.54	-0.89	0.90	-0.65	-0.13	1.00	0.68	-0.48
Urban Index	-0.29	-0.15	-0.48	0.86	-0.16	-0.58	0.68	1.00	-0.81
Year Built	-0.06	-0.03	0.37	-0.75	-0.24	0.73	-0.48	-0.81	1.00

Table A.2 shows the average values for neighborhood characteristics calculated for each site using census data and a weighted average.

Site	Median Income	Total Population	% of Units Rented	Median Year Built	House Value ($)	Average Rent ($)	Age of Population
Tuttle	22731	3912	82.8	1958	121320	763	23
Kenny	53993	3217	43.7	1966	191478	997	45
Rush Run	79054	2474	20.7	1966	226800	1095	50
Casto	60508	5180	39.8	1974	131637	908	33
Elk Run	51098	6884	32.2	1991	114500	836	32
Cherry Bottom	51086	3845	46.0	1987	172225	714	33
Woodside	80387	6022	33.63	1989	210212	972	39

Table A.3 shows summary results from the top five models of the candidate model set using basal area as response variable, reporting the coefficient, standard error, t-value, and p-value, including the variable(s) used in each model to show effect on addition of variables on model statistics.

Model	Variable	Coefficient	Standard Error	T-value	P-Value
1	Age	0.0135	0.0172	0.781	0.4701
2	Total Population	-1.692e-04	6.758e-05	-2.504	0.0542
3	Urban Index	0.3323	0.2420	1.373	0.2280
4	Year Built	-0.0247	0.0058	-4.221	0.0083
7	Year Built Age	-0.0242 0.0113	0.0053 0.0078	-4.578 1.461	0.0102 0.2177

Table A.4 shows summary results from top five models of the candidate model set using Shannon Diveristy Index as the response variable, reporting the coefficient, standard error, t-value, and p-value, including the variable(s) used in each model to show effect on addition of variables on model statistics.

Model	Variable	Coefficient	Standard Error	T-value	P-Value
1	Age	0.0025	0.0026	0.943	0.3891
2	Total Population	-2.30e-05	1.27e-05	-1.817	0.1289
3	Urban Index	0.0408	0.0405	1.008	0.3597
4	Year Built	-0.0030	0.0014	-2.176	0.0815
7	Year Built Age	-0.0030 0.0022	0.0014 0.0020	-2.151 1.104	0.0978 0.3313

Table A.5 ranks the top three most abundant species in each site, with "First" being the most abundant, "Second" being the second most abundant, and "Third" being the third most abundant species at a given site. "Count" column refers to the number of each species present in that site.

Site	*First*	*Count*	*Second*	*Count*	*Third*	*Count*
Tuttle	Box Elder	288	Mulberry	161	Honeysuckle	85
Kenny	Honeysuckle	435	Box Elder	133	Buckeye	49
Rush Run	Black Maple	145	Honeysuckle	119	Box Elder	111
Casto	Box Elder	45	Buckeye	26	Black Walnut	11
Elk Run	Honeysuckle	50	American Elm	30	Box Elder	23
Cherry Bottom	Box Elder	35	Sugar Maple	16	Grapevine	12
Woodside	Buckeye	62	Box Elder	37	Paw Paw	22

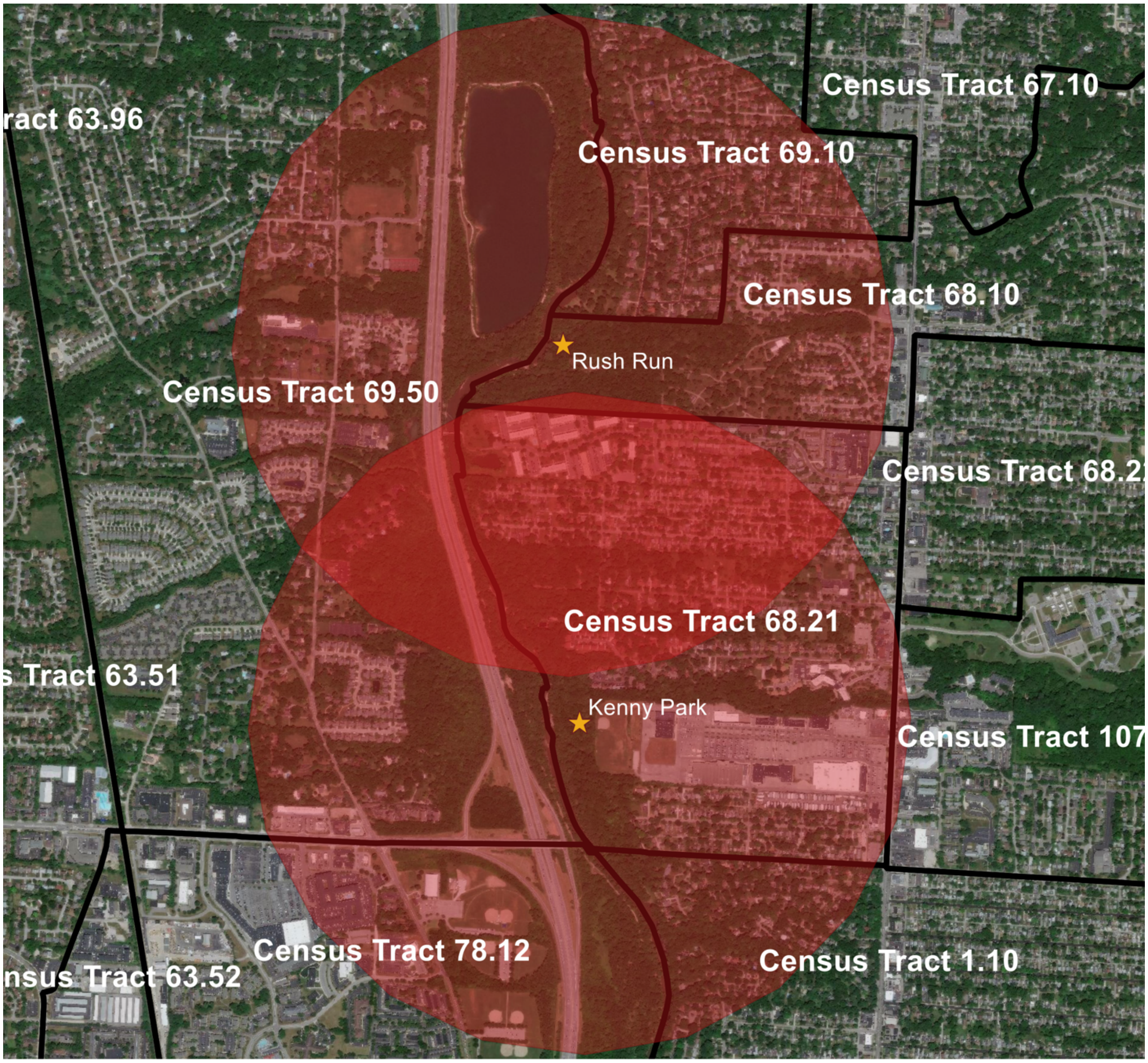

Figure A.1.1: Map of Rush Run and Kenny Parks with 1-km buffer around center points, showing background of census tracts. Census tracts were weighted based on area contained in 1-km buffer as described in Methods. Data retrieved from US Census Bureau.

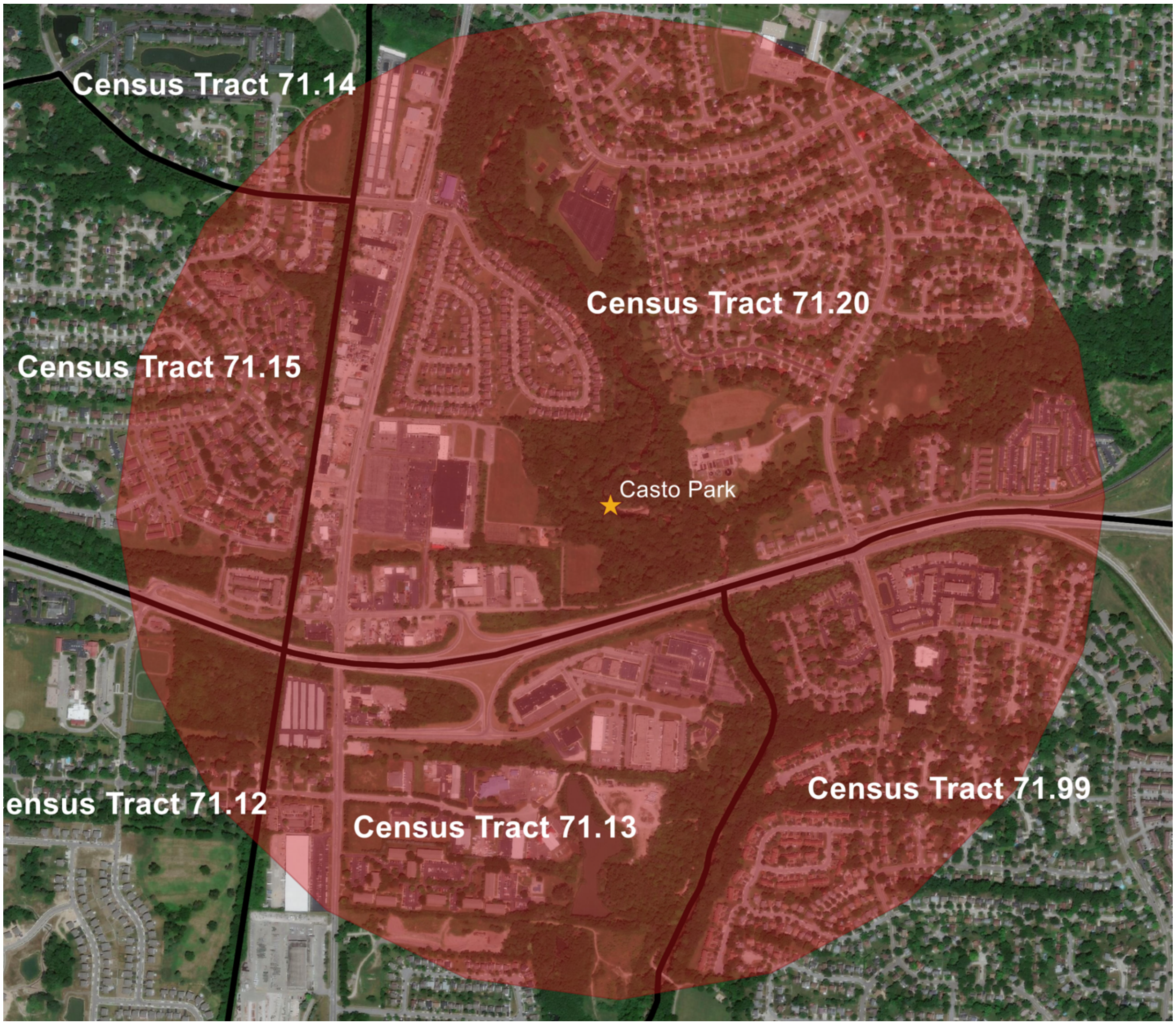

Figure A.1.2: Map of Casto Park with 1-km buffer around center points, showing background of census tracts. Census tracts were weighted based on area contained in 1-km buffer as described in Methods. Data retrieved from US Census Bureau.

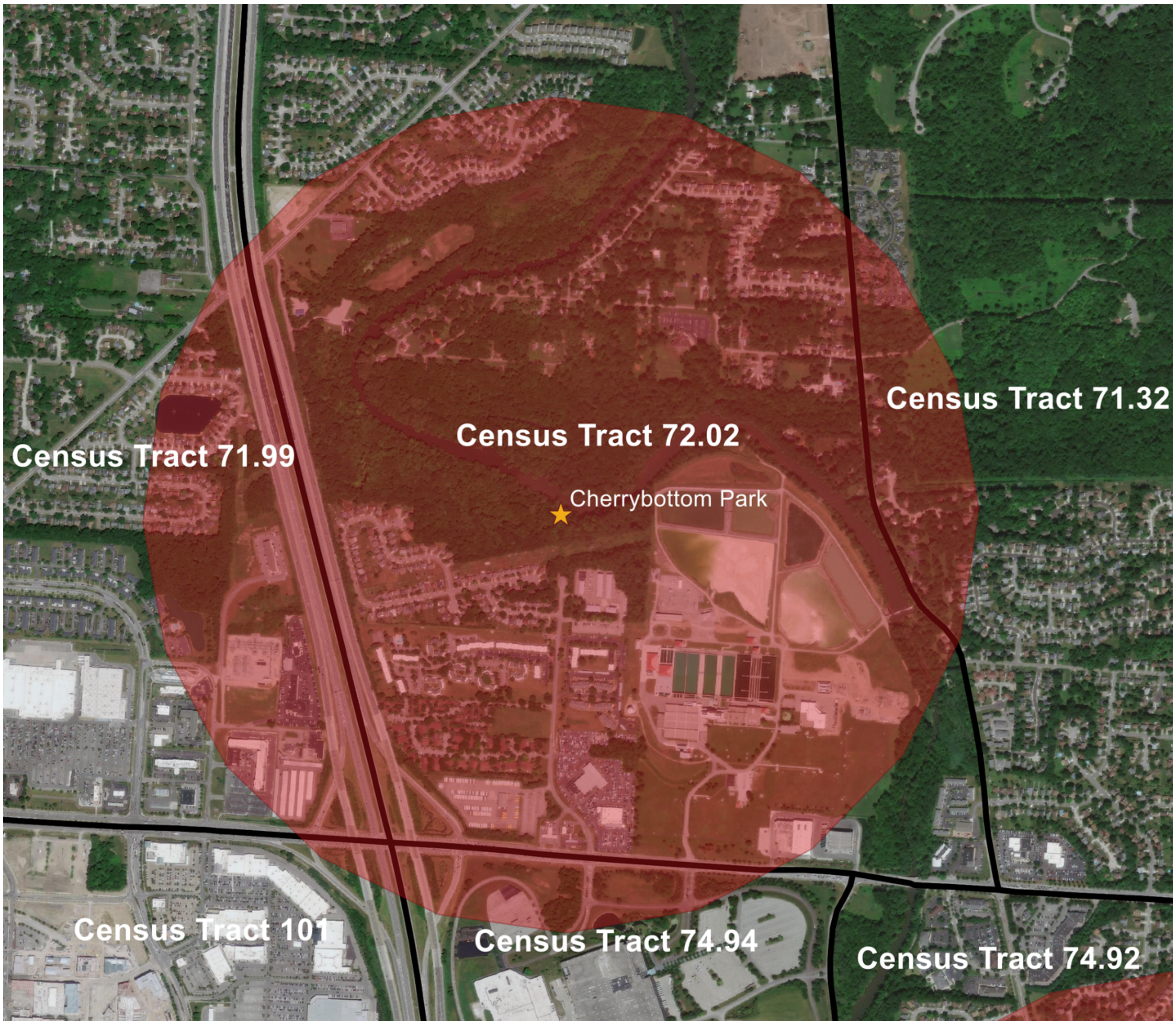

Figure A.1.3: Map of Cherrybottom Park with 1-km buffer around center points, showing background of census tracts. Census tracts were weighted based on area contained in 1-km buffer as described in Methods. Data retrieved from US Census Bureau.

Figure A.1.4: Map of Elk Run Park with 1-km buffer around center points, showing background of census tracts. Census tracts were weighted based on area contained in 1-km buffer as described in Methods. Data retrieved from US Census Bureau.

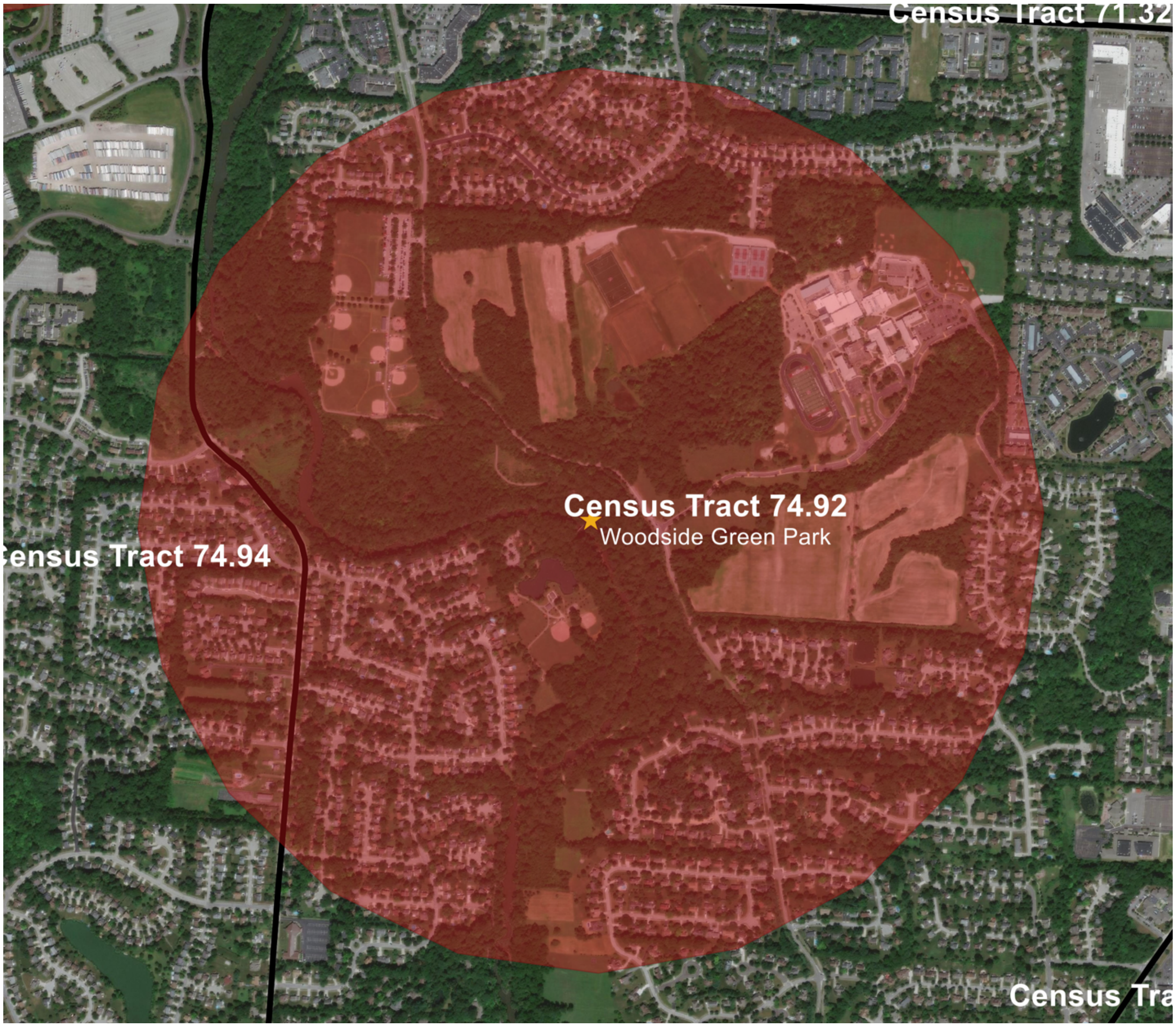

Figure A.1.5: Map of Woodside Green Park with 1-km buffer around center points, showing background of census tracts. Census tracts were weighted based on area contained in 1-km buffer as described in Methods. Data retrieved from US Census Bureau.